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CSC448 Artificial Intelligence

12.20.2023

Final Report

Abstraction

The objective of this project is to refine the accuracy of our spam detection model, ensuring a high level of precision in distinguishing between spam and legitimate emails. Secondly, our focus extends to increasing security, aiming to decrease the vulnerabilities associated with phishing attacks and malicious emails, thereby fostering a safer online environment for all users. In addition to these primary goals, we aspire to materialize a functional prototype using Viola. As a team, we successfully attained an accuracy score of 97% for the random forest model, solidifying its role as a foundational background model for Viola.

Introduction

Addressing the challenge of differentiating between spam and non-spam emails is the main focus of our project's classification task. Even while current algorithms can categorize emails, spam continues to find its way into our inboxes, suggesting that further improvement is necessary. We focused on developing a classification system that is more accurate and reliable, reducing the amount of spam emails that reach an individual's user's inbox. Throughout our project, we employed six distinct models: Naive Bayes (multinomial naive bayes), SVM, Logistic Regression, Random Forest, Gradient Boosting, and Decision Tree. These models played a crucial role in our efforts to identify the most accurate model for accurate email classification.

Pre-processing

Combining Data:

Further insights into this data combining process are documented in our "Combining Data.ipynb".

To prepare our data for a model, a crucial step involves data cleaning. Initially, we identified 2 datasets: spam.csv and spam_or_not_spam.csv. Here are the specifics of each datasets:

- spam.csv
    - df2 in "Combining Data.ipynb"
    - 2 columns, 5k rows
    - Columns: Category, Message
    - Column Category: ham = not-spam, spam = spam
    -

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

- spam_or_not_spam.csv
    - df3 in "Combining Data.ipynb"
    - 2 columns, 3k rows
    - Columns: Email, Label
    - Column Label: 0 = not-spam, 1 = spam
    -

	email	label
0	date wed NUMBER aug NUMBER NUMBER NUMBER NUMB...	0
1	martin a posted tassos papadopoulos the greek ...	0
2	man threatens explosion in moscow thursday aug...	0
3	klez the virus that won t die already the most...	0
4	in adding cream to spaghetti carbonara which ...	0

Both datasets exhibited similar formatting. They both have 2 columns, one indicating spam or not spam, another column providing the string of email messages. To combine it, I've decided to first address the column indicating spam/not-spam. I've decided to indicate spam/not-spam using 1 and 0, respectively. So, in df2 I replaced "ham" with "0" and "spam" with "1". Then, I relabeled the column names in df2 to be "label" and "email":

```
In [9]: ## change df_2 column name and values of category to 0 and 1 to match df_3
        df_2["Category"] = df_2["Category"].replace('ham', '0')
        df_2["Category"] = df_2["Category"].replace('spam', '1')
```

```
In [10]: df_2.rename(columns = {"Category" : "label"}, inplace = True)
         df_2.rename(columns = {"Message" : "email"}, inplace = True)
```

To prepare for merging, I matched the same order of columns as df2, I re-arranged df3 columns to be "label" then "email" instead of its original "email" then "label":

```
In [11]: df_3 = df_3[['label', 'email']] # switch around label and email to align the columns
```

```
In [12]: df_2.head()
```

Out[12]:

	label	email
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

```
In [13]: df_3.head()
```

Out[13]:

	label	email
0	0	date wed NUMBER aug NUMBER NUMBER NUMBER NUMB...
1	0	martin a posted tassos papadopoulos the greek ...
2	0	man threatens explosion in moscow thursday aug...
3	0	klez the virus that won t die already the most...
4	0	in adding cream to spaghetti carbonara which ...

To merge the 2 dataframes, I concat them vertically:

```
In [14]: # combine vertically
         df_combined = pd.concat([df_2, df_3], ignore_index=True)
```

The final combined dataframe: df_combine looks like this:

	label	email
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

Then I removed any NULL values and eliminated any duplications:

```
In [17]: # drop duplicates
         df_combined = df_combined.drop_duplicates()
```

```
In [30]: ## drop NULL value
         df_combined = df_combined.dropna(subset=['email'])
```

Lastly, I prepared the new data, df_combine, to be converted to CSV file for further Exploratory Data Analysis (EDA) and data preprocessing. The resulting dataset CSV file is characterized by the following details:

- combined_data_clean.csv
    - 2 columns, 8k rows
    - Columns: Label, Email
    -

	label	email
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

The EDA is delved into further details in the next portion. We identified 515 emails out of 8,029 to be in foreign languages. Contemplating the option of translation, we decided against it due to

potential inaccuracies that could disrupt the model's outcomes. Consequently, we collectively opted to omit these rows from our dataset. We conducted word and frequency counts, employing unary, bigram, and trigram n-gram models on emails categorized as spam and not-spam. To standardize the process, we converted all words to lowercase, tokenized the strings, and eliminated stopwords. Further details on the cleaning and exploration stages can be found in each team member's respective Exploratory Data Analysis (EDA) notebook: Alice EDA, Emily EDA, Lily EDA.

Visualizations/EDA:

Again, we used the df_combined to create the following analysis:

Alice: All of my visualizations EDA can be found in:

https://github.com/AliceLiu17/csc448_final/blob/main/code/alice/EDA_preprocessing_Alice.ipynb

I renamed df_combined to be df in my analysis:

Initial exploration included shape and unique values. When I reviewed the unique values, I discovered that there was foreign language in our dataset:

```
r order NUMBER NUMBER hours during business hours thank you for your time and i hope to hear from you soon ',
       ' hello this is chinese traditional 子 件 NUMBER世 o最有效的宣 鞣绞剑 您想 地NUMBER f人同一 r刻知道您的 v告 幔磕 想方
便快捷的宣 骼 的企 i 幔 您想在商 i 中步步 紫 c 幔 您想一次 碛 在商 i客 幔 越 碓蕉嗟恼 查表明 w路直 n 成 未 i n方式的主流 而e mail
⑹蔷w上 i n最常用也是最 用的工具 其特 c v r效高 r格低 emarketer估 美 有NUMBER 的中等 模公司 常 用 子 件 m行 i n活 印 部分 v告媒
w平均回 率比 average response rate ranges NUMBER NUMBER NUMBER 普通横幅广告 banner ads NUMBER NUMBER 普通信件 direct mai
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Rhk 一周NUMBER f NUMBERhk 保 c w站日 l 量提升NUMBER以上 包月群 l 一月NUMBER f NUMBERhk 保 c w站日 l 量提升NUMBER以上 件 w N
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人一天之 都知道你的 a品 y 那麽 v告 件投放就是你最好的解 q方案 它的 r格是所有 髓 r格中最低 但又是最有效的 c遇每 r每刻都等待著你 也 s你
正是用了 拥 髓菏侄危 而打垮了所有的 κ帧ｚｓ快行 影桑 你的企 i 公司立即掌握商 i 髓降拿 v告e mail 是普通 厩n i所不能比 m的 m及付款方式
本公司 氖戮w路 v告多年 宣 髁χ任痪又 第四大 w路 v告商之一 我 有 ｉt的技 g人 t和高速 i的服 障到y 氖麓隧 工作 必 您的企 i提供最迅捷 最
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      dtype=object)
```
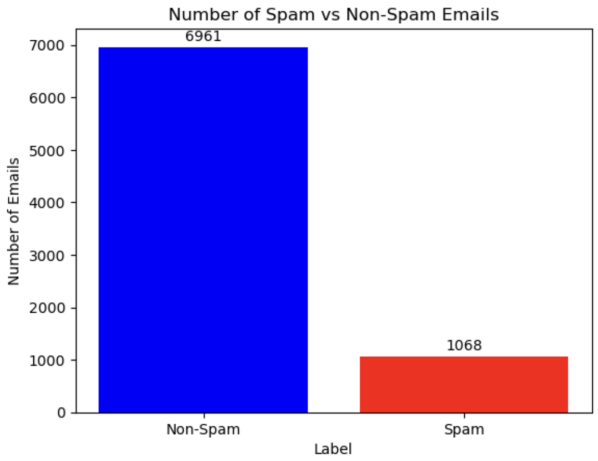

I then explored the ratio of spam vs. not-spam in our df, by using a bar graph. We have 6961 non-spam and 1068 spam emails in our dataset:



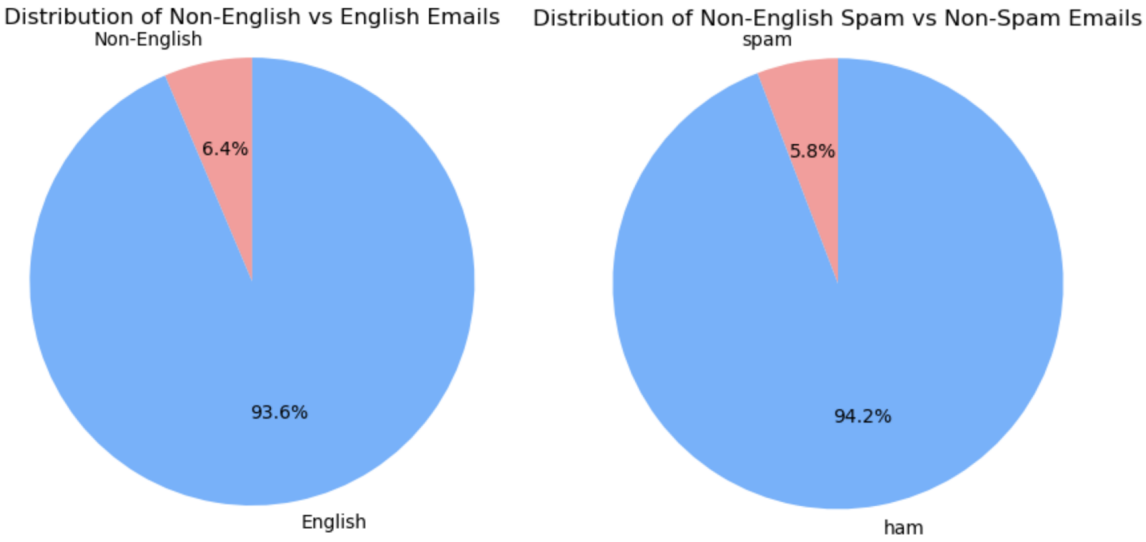
Then I addressed the foreign language. I used the langdetect library to detect what languages were English and non-English, and generated a ratio of how many emails were English and non-English, and of the non-English emails, how many emails were spam vs. non-spam. These are the insights I've discovered:

```
print("Number of non-english emails:", non_english_rows_count)
```

```
Number of non-english emails: 515
```

```
print("Spam/Non-spam ratio for non-english emails:")
print(non_english_labels.value_counts())
```

```
Spam/Non-spam ratio for non-english emails:
0    485
1     30
Name: label, dtype: int64
```



Since there were only 515 non-english emails out of 8,029 emails, we've decided to drop the non-English emails, as including it and translating them can be inaccurate, which would throw off the final result of the model.

I then wanted to gain a better insight as to what words in the email message would indicate spam and not-spam. To do this, it required extra data preprocessing such as:

1. Conversion to lowercase: so that same words are recognized as the same
2. Tokenization: separate each word so we can analyze each word individually in a string
3. Remove Stopwords: stopwords like "is", "like", "the", are common english terminology to generate sentences. When generating word frequency, these stopwords can throw off the result and it won't help with generating better insights.

This is the code done:

```
In [16]: # convert everything to lower case
         df_en["email"] = df_en["email"].str.lower()
```

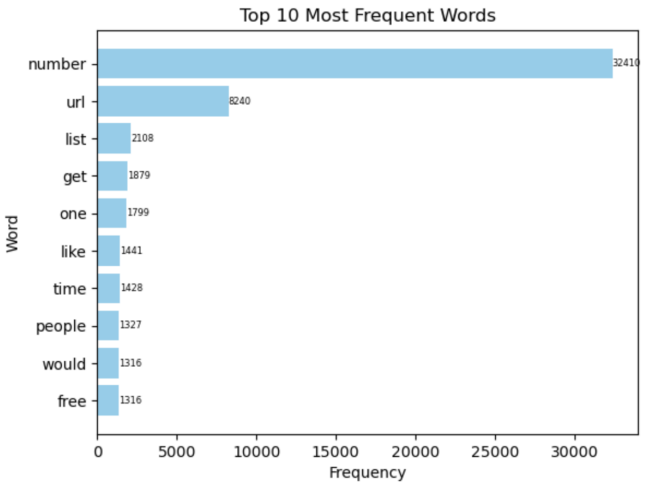
```
In [18]: # tokenize and count words
         def tokenize_count(text):
             words = re.findall(r'\b\w+\b', text)
             return Counter(words)
```

```
In [19]: # remove stop words
         stop_words = set(stopwords.words('english'))

         def remove_stopwords(text):
             words = word_tokenize(text)
             filtered_words = [word for word in words if word.lower() not in stop_words and re.match(r'\b\w+\b', word)]
             return ' '.join(filtered_words)
```

Using the preprocessing functions, I inputted my dataframe to the functions and conducted a unary, bigram, and trigram for n-gram analysis. These were the results:

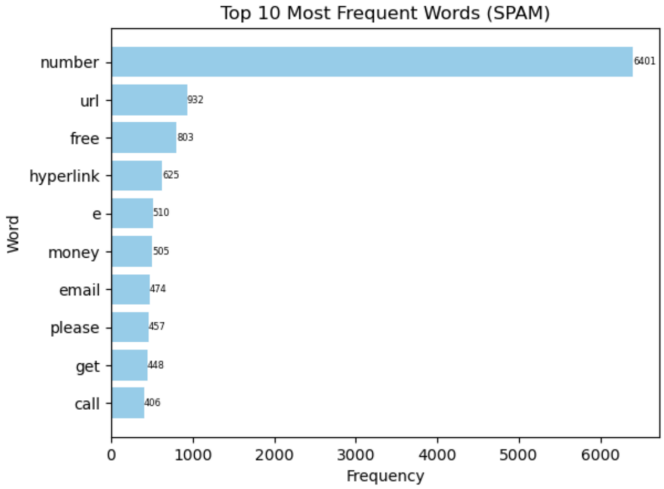
Unary for overall dataframe:

	Word	Frequency
1479	number	32410
436	url	8240
4535	list	2108
612	get	1879
551	one	1799
60	like	1441
384	time	1428
684	people	1327
16	free	1316
675	would	1316



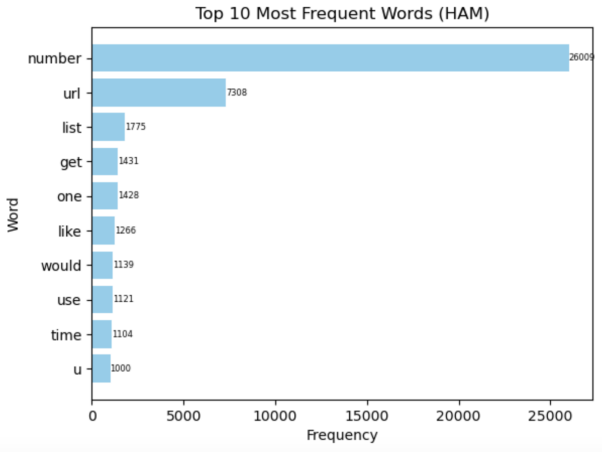
Unary for overall spam dataframe:

	Word	Frequency
515	number	6401
2795	url	932
0	free	803
2781	hyperlink	625
392	e	510



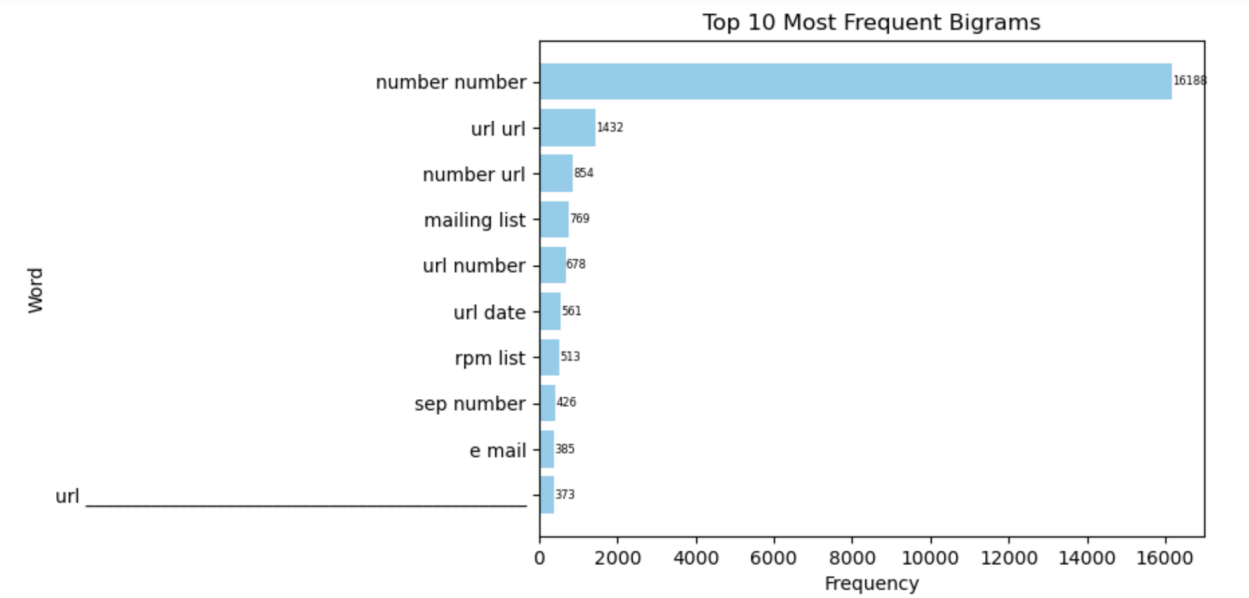
Unary for overall non-spam dataframe:

	Word	Frequency
1084	number	26009
291	url	7308
3464	list	1775
433	get	1431
373	one	1428



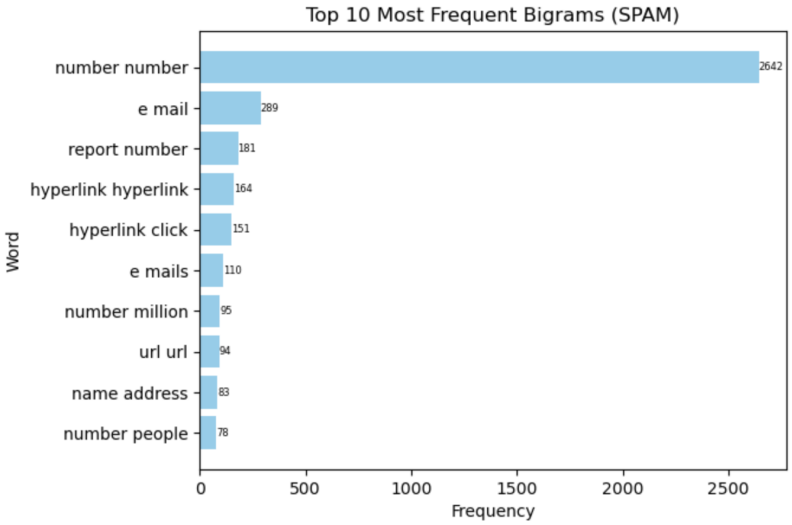
Bigram for overall dataframe:

	Bigram	Frequency
18182	(number, number)	16188
32447	(url, url)	1432
35250	(number, url)	854
32444	(mailing, list)	769
33764	(url, number)	678



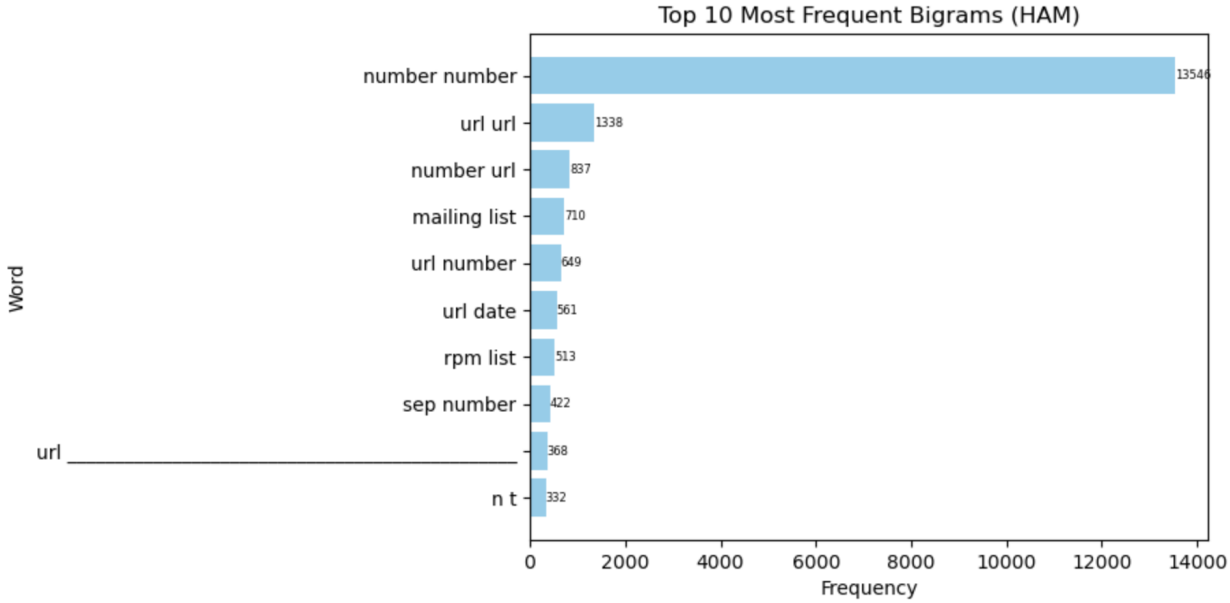
Bigram for overall spam dataframe:

	Bigram	Frequency
6623	(number, number)	2642
6608	(e, mail)	289
9604	(report, number)	181
7477	(hyperlink, hyperlink)	164
6585	(hyperlink, click)	151



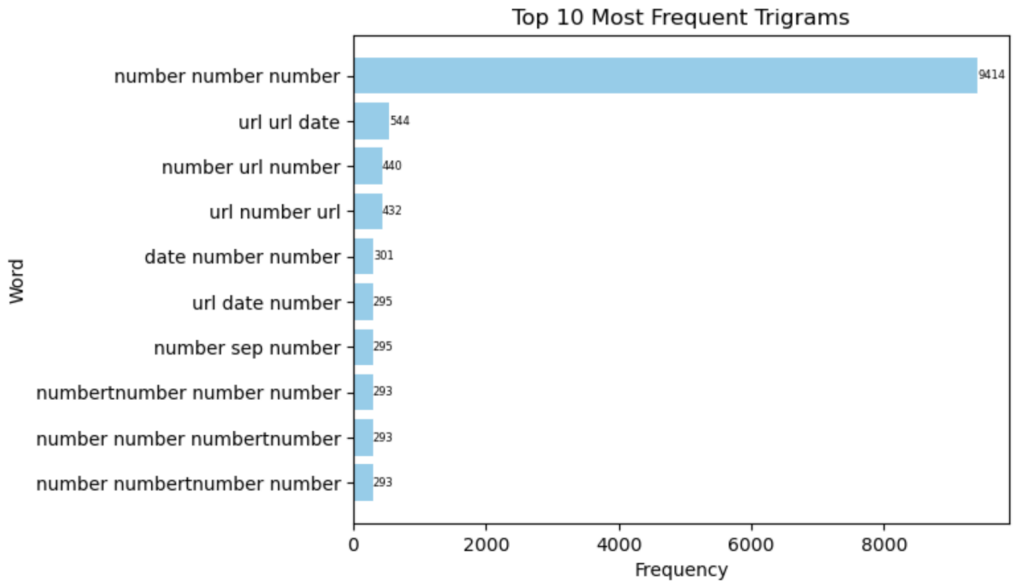
Bigram for overall non-spam dataframe:

	Bigram	Frequency
14151	(number, number)	13546
26149	(url, url)	1338
28957	(number, url)	837
26146	(mailing, list)	710
27469	(url, number)	649



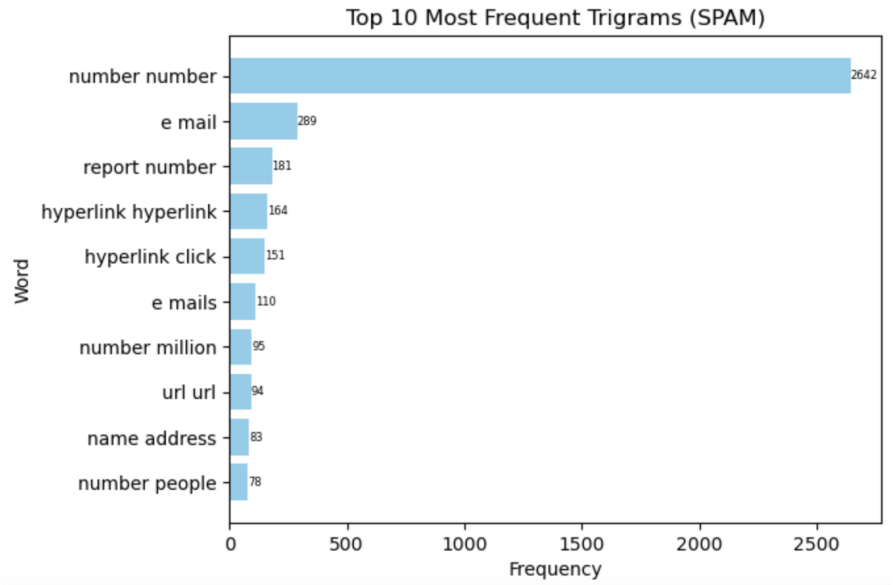
Trigram for overall dataframe:

	Trigram	Frequency
33559	(number, number, number)	9414
45799	(url, url, date)	544
41336	(number, url, number)	440
41337	(url, number, url)	432
45801	(date, number, number)	301



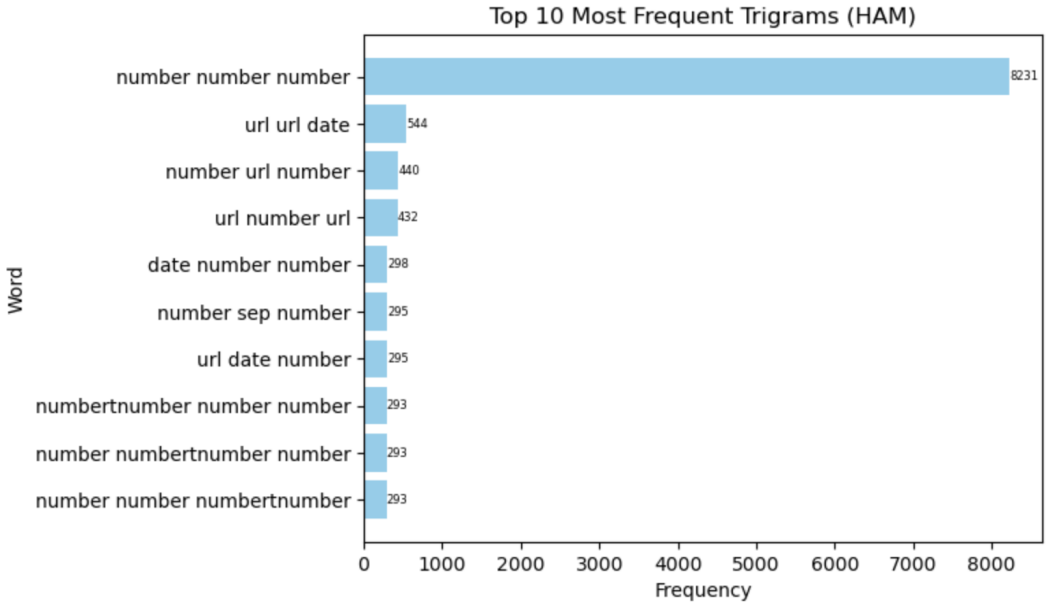
Trigram for overall spam dataframe:

	Trigram	Frequency
6623	(number, number)	2642
6608	(e, mail)	289
9604	(report, number)	181
7477	(hyperlink, hyperlink)	164
6585	(hyperlink, click)	151



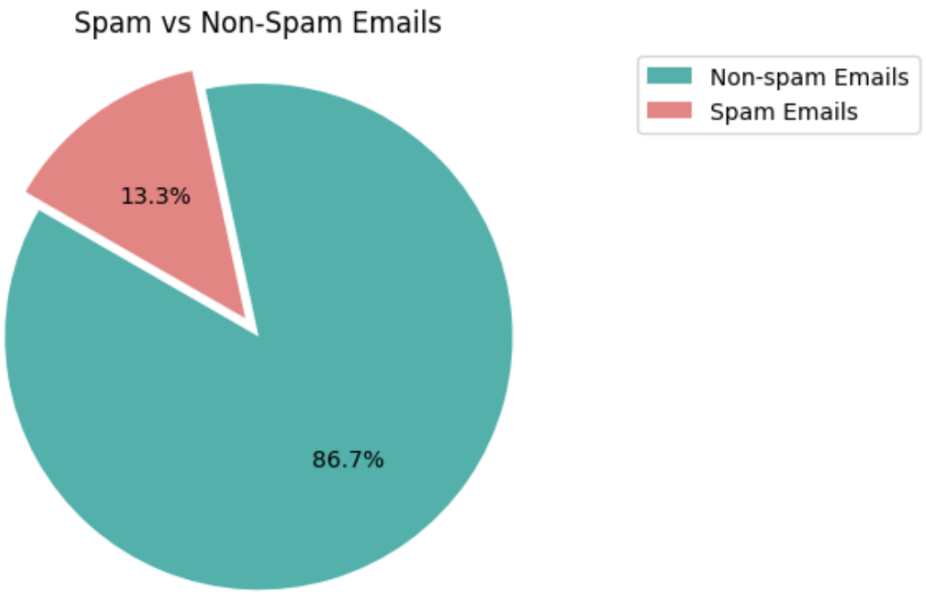
Trigram for overall non-spam dataframe:

	Trigram	Frequency
26392	(number, number, number)	8231
38633	(url, url, date)	544
34170	(number, url, number)	440
34171	(url, number, url)	432
38635	(date, number, number)	298

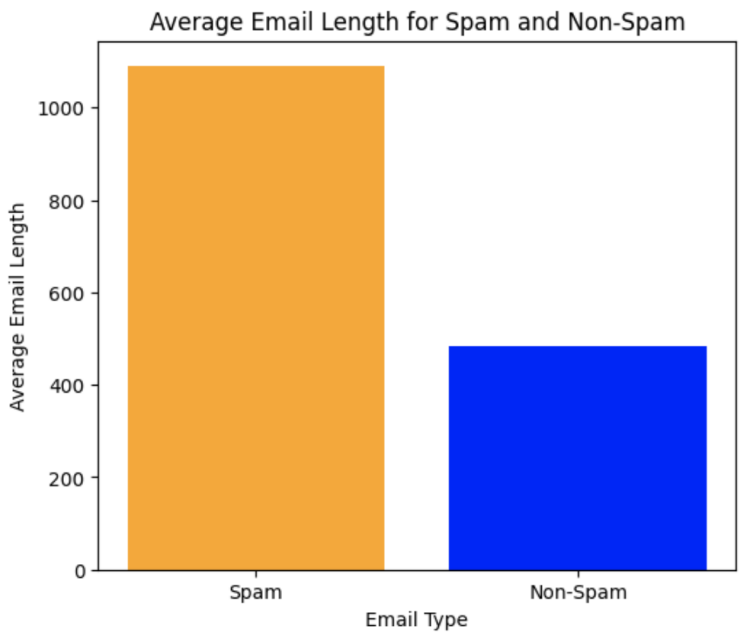


These results tell me that a notable spam indicator that's not in a non-spam email is where the message indicates the user to click on a hyperlink, asking the user for money, or urging the user to call.

Emily: All of my visualizations that are shown below can be found in this Github path: code/emily/data_analysis.ipynb or the link: https://github.com/AliceLiu17/csc448_final/blob/main/code/emily/data_analysis.ipynb



I created a pie chart visualization. This visualization is to demonstrate the distribution of spam and non-spam emails in the combined dataset that we have created. In this chart, I used a light sea green color to represent non-spam emails, and a coral color to represent spam emails. As you can see, we had more non-spam emails than spam emails in this dataset. Specifically, we have about 87% non-spam emails and 13% spam emails.

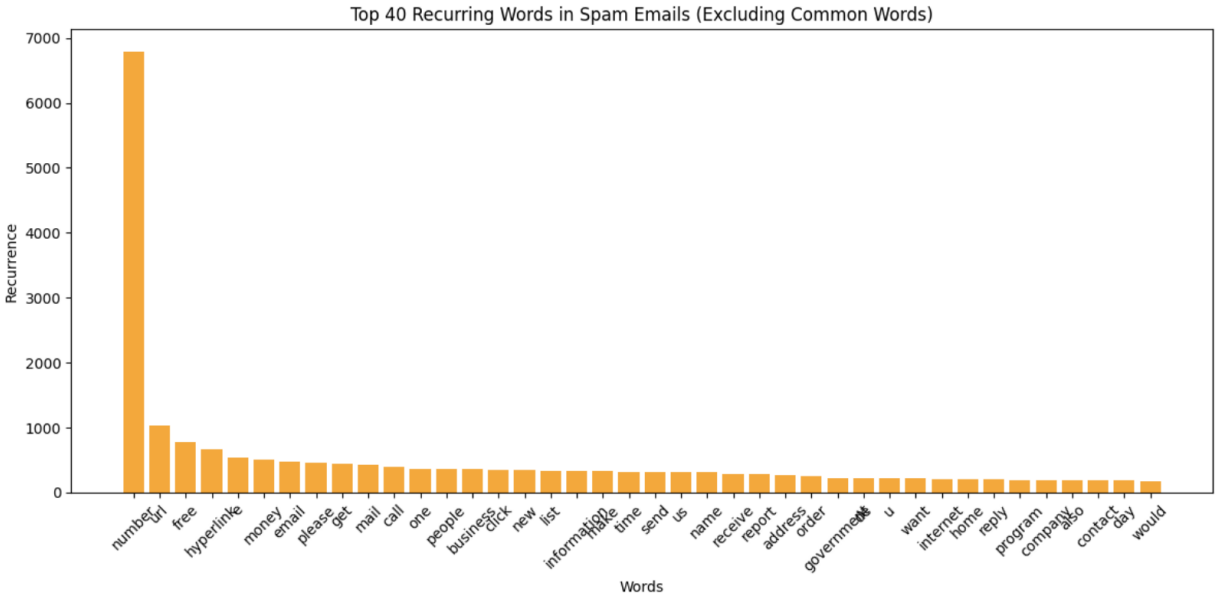


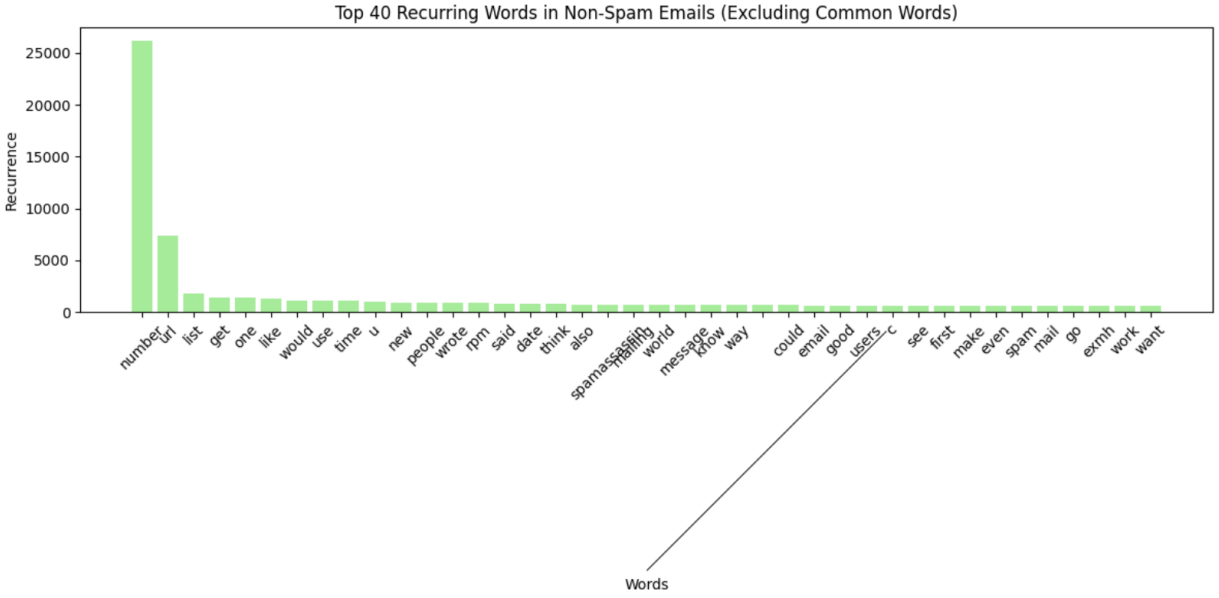
I created a bar chart visualization. This visualization is to demonstrate a visual pattern in the average lengths of the two types of emails. In this chart, I used a yellow-orange color to represent spam emails, and blue to represent non-spam emails. As you can see, spam emails had on average more than 1000 characters in their text, while non-spam emails were more than 400 characters, but less than 600 characters. This demonstrates that spam emails typically have more characters being used in their email.

```
stopwords = set(stopwords.words('english'))

# filter out the common words(stopwords)
def preprocess_and_filter(emails):
    words = ' '.join(emails).split()
    return [word.lower() for word in words if word.lower() not in stopwords]

# filter out the stopwords in each of the types of email
filtered_spam = preprocess_and_filter(spam_emails)
filtered_not_spam = preprocess_and_filter(not_spam_emails)
```

The next visual I made was another bar chart. However, this was when I realized that there were many common words that were being shown previously when I had created this, so above is a code

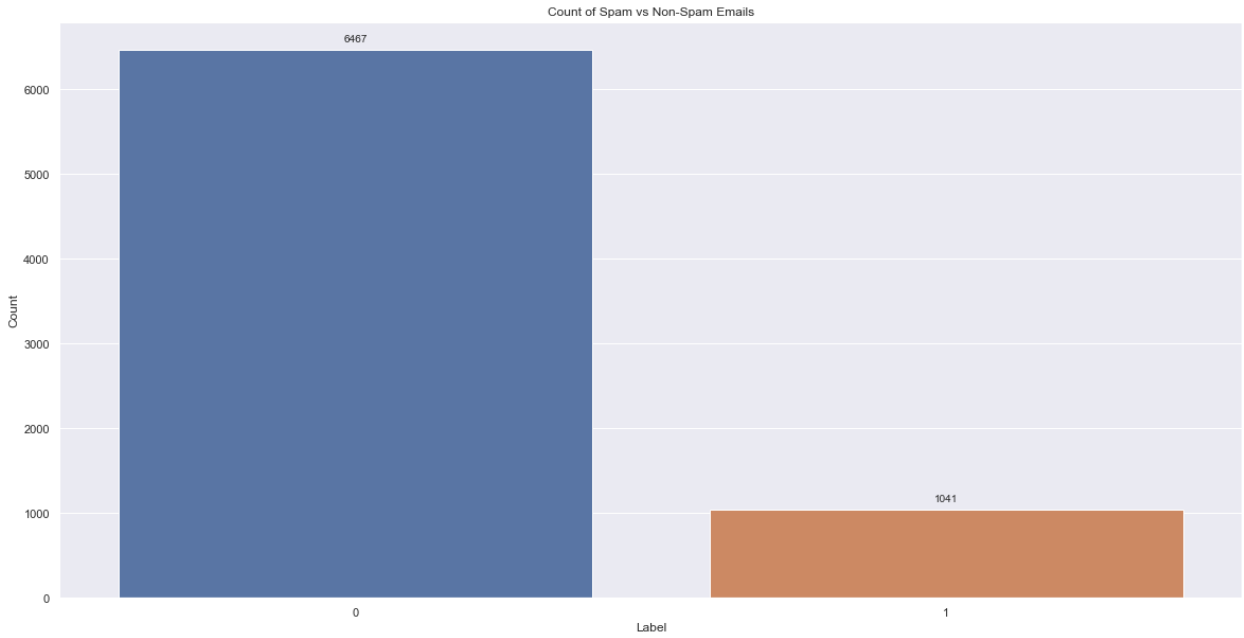
snippet of removing common words and lowercasing the text in the emails. The reason for lowercasing the text in the emails is so that it can be consistent throughout.



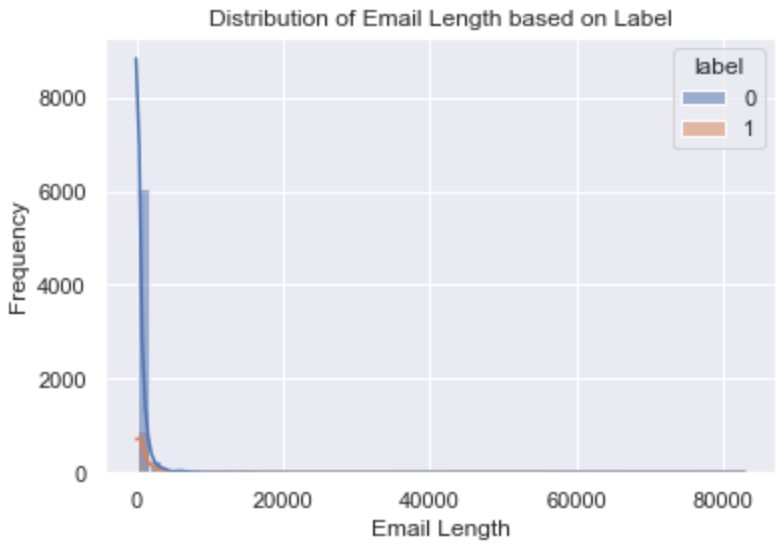


This visual is now showing the top 40 recurring words that appear in spam and non-spam emails. As you can see from the visuals, a lot of the words in spam emails had mentioned text like link, money, and click. This demonstrates a relation to phishing and scam messages. While in non-spam emails, it had mentioned text like messages, email, work, and words, which demonstrates a relation to daily life and common communication.

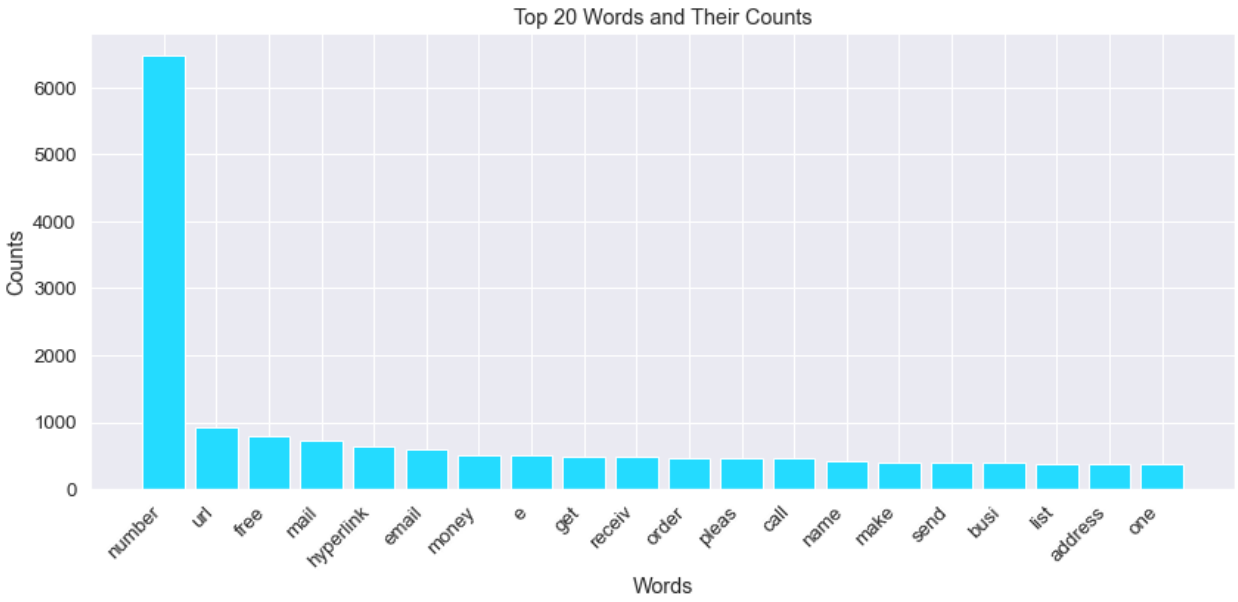
Lily: This is the link to my notebook with all the visualizations (https://github.com/AliceLiu17/csc448_final/blob/main/code/lily/EDA%20and%20Preprocessed.ipynb)



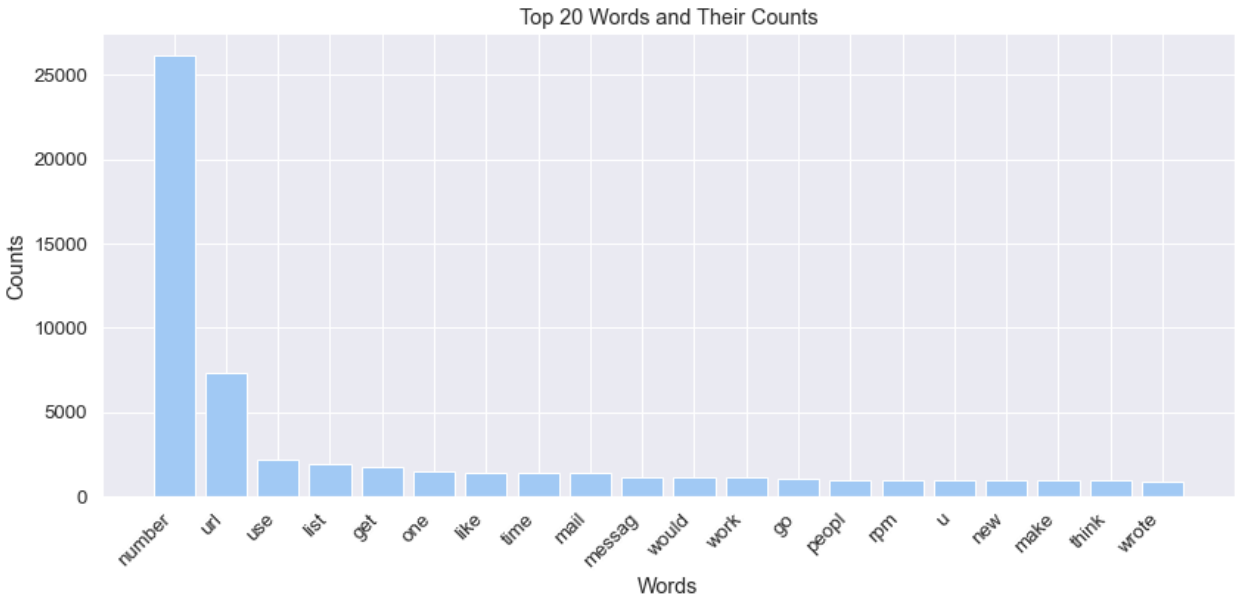
I created a bar graph to display the ratio of spam versus non-spam emails in my dataset to visually represent the distribution and imbalance between these two classes. In our case, we have 6467 non-spam emails and 1041 spam emails, and visualizing this through a bar graph helps to illustrate the class distribution.



I made a histogram plot to visualize the distribution of email lengths and it helps understand the role of email length in distinguishing between spam and non-spam emails. It provides insights for feature selection, model interpretation, and potential enhancements, thereby contributing to more effective email classification models. I can see that non-spam emails tend to have longer lengths whereas spam emails tend to have shorter lengths which makes sense. There is an overlap between both non-spam and spam emails so those emails that fall in between might be harder to differentiate but there are other features we can use such as the words itself.



This graph shows the top 20 words and their frequency for spam emails. The most frequent word used is number and url. This might be because in many emails, they are always trying to get you to click on this url link or trying to scam you into calling a certain number such as free and hyperlink. It's interesting to see how in both spam and non-spam emails, the most frequent words are number and url. For the rest of it, you can see some misspelled words because mainly in spam emails, they misspell words so it's obvious if they are spam emails. I can see money, get, receive and order which are common words I see in my spam emails as well.



This graph shows the top 20 words and their frequency for non spam emails. The most frequent word used is number and url. This might be because in many emails, they are always referring to number X in this pdf or please call my number X if there are any questions. In the corporate world, they are usually referring to a certain url as well or emailing about where to find that url link. For the rest of them, you can see free, mail, email, send, and address which all correlate to real-world emails between professionals such as when are you free to schedule a meeting or where do you want to meet with people.

Continue Data Preprocessing:

As a group, we've continued with the decision of the removal of foreign language data (ALICE EDA) and the task of removing foreign language data points, conversion to lowercase, string tokenization, and stopword removal (EMILY EDA). This combination was executed in the "preprocessing.ipynb" notebook. The outcomes were then distilled into a new CSV file:

- preprocessed_english.csv
    - 3 columns, 8k rows

- Columns: Label, Email, processed_email

	label	email	processed_email
0	0	Go until jurong point, crazy.. Available only ...	[go, jurong, point, crazy, .., available, bugi...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	[free, entry, 2, wkly, comp, win, fa, cup, fin...
3	0	U dun say so early hor... U c already then say...	[u, dun, say, early, hor, ..., u, c, already, ...
4	0	Nah I don't think he goes to usf, he lives aro...	[nah, n't, think, goes, usf, lives, around, th...
5	1	FreeMsg Hey there darling it's been 3 week's n...	[freemsg, hey, darling, 's, 3, week, 's, word,...

This file is used in our modeling portion of the project.

Modeling

In our project, we employed a range of machine learning algorithms chosen based on their perceived suitability and potential efficacy for addressing the project requirements.

1. Naive Bayes (Multinomial Naive Bayes)
    a. The Naive Bayes classifier, specifically the Multinomial Naive Bayes variant, was selected for its simplicity and effectiveness in text classification tasks. It is a classification algorithm that's particularly well-suited for text-based data, such as classifying documents or emails into categories like spam or not spam, topics, sentiment analysis, etc. By leveraging the probabilities of word occurrences, this model assumes independence between features and performs remarkably well even with relatively small datasets. Its computational efficiency and ability to handle large feature spaces made it a suitable choice for our project.
2. Support Vector Machine (SVM)
    a. SVM is a powerful classifier that was utilized due to its ability to effectively separate data points using a hyperplane, optimizing the margin between classes. It excels in high-dimensional spaces and was expected to perform well in our text-based classification task by identifying complex decision boundaries.

3. Logistic Regression
    a. Logistic Regression, aka Logit, is a classification machine learning algorithm that uses labeled data to predict a discrete outcome by assigning a predicted probability to each decision. Its simplicity and interpretability make it a popular choice for binary classification tasks. In this project, it was used as a baseline model to benchmark the performance of more complex algorithms.
4. Random Forest
    a. Random Forest algorithm is an ensemble method based on decision trees, and was employed for its capability to handle non-linear relationships within data and reduce overfitting. By constructing multiple decision trees and aggregating their outputs, this model aimed to enhance classification accuracy and robustness.
5. Gradient Boosting Models
    a. Gradient Boosting Models, including Gradient Boosting Classifier, were chosen for their ability to combine multiple weak learners (typically decision trees) into a strong learner. The iterative nature of boosting techniques helps to correct errors made by previous models, potentially leading to superior predictive performance.
6. Decision Tree
    a. Decision trees classify the examples by sorting them down the tree from the root to some leaf/terminal node, with the leaf/terminal node providing the classification of the example. Decision Trees were explored to create a clear visualization of decision-making processes. These models are intuitive, representing decisions as branches and nodes, making them easy to interpret and explain.

The selection of these diverse models aimed to explore various approaches to classifying spam and non-spam emails. This strategy allowed for a comprehensive evaluation of performance across

different algorithmic paradigms, enabling us to find the most suitable model for our specific project.

We divided the models equally among the 3 members:

Model	Assigned
Gradient Boosting (GBDT), Random Forest (RF)	Alice
Logistic Regression (LR), Support Vector Machine (SVC)	Emily
Naive Bayes (NB), Decision Trees (DT)	Lily

Alice: This is the link to my notebook with the models assigned:

https://github.com/AliceLiu17/csc448_final/blob/main/code/alice/Modeling.ipynb

Again, using the final dataset that's been preprocessed and cleaned: preprocessed_english.csv

Initialized CountVectorizer and TfidfVectorizer to convert text data into numerical features, since our data are essentially all strings. Then I limited the maximum number of features to be 3000.

Then, I prepared the data by creating a feature matrix X, and target variable y. We want to predict if something was spam, therefore, y will be column 'label', and X is 'processed_email'. The data is then split into training and testing sets.

```
# create a training and testing set to train
cv = CountVectorizer()
tfid = TfidfVectorizer(max_features = 3000)

X = tfid.fit_transform(df['processed_email'])
y = df['label'].values

X_train, X_test , y_train, y_test = train_test_split(X,y,test_size = 0.20, random_state = 45)
```

My focus was Gradient Boosting and Random Forest, therefore, I initialized the models, then created a dictionary so that we can combine the models later more efficiently.

```
rfc = RandomForestClassifier(n_estimators = 50, random_state = 2 )
gbdt = GradientBoostingClassifier(n_estimators = 50, random_state = 2)

# models to test:
models = {
    'RF': rfc, # random forest
    'GBDT': gbdt   # gradient boosting
}
```

Then in the train_classifier function, we train the model and generate the model evaluation. I've created the model evaluation using accuracy, precision, recall, f1 score, and auc-roc. Each score explanation will be explained in the analysis portion of the paper.

```
# train the model and compute model evaluation
def train_classifier(clfs, X_train, y_train, X_test, y_test):
    models.fit(X_train,y_train)
    y_pred = models.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred) # accuracy
    precision = precision_score(y_test, y_pred) # precision
    recall = recall_score(y_test, y_pred) # recall
    f1 = f1_score(y_test, y_pred) # f1

    # If the model provides decision scores, calculate AUC-ROC
    if hasattr(models, 'decision_function'):
        y_scores = models.decision_function(X_test)
        auc_roc = roc_auc_score(y_test, y_scores)
    elif hasattr(models, 'predict_proba'):
        # For models with predict_proba
        y_probs = models.predict_proba(X_test)[:, 1]
        auc_roc = roc_auc_score(y_test, y_probs)
    else:
        auc_roc = None  # AUC-ROC not available for this model


    return accuracy , precision, recall, f1, auc_roc
```

In [5]:

```
# display the model evaluation from train_classifier
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []
auc_roc_scores = []

for name, models in models.items():
    current_accuracy, current_precision, current_recall, current_f1, current_aucroc = train_classifier(models, X_
    print()
    print("For: ", name)
    print("Accuracy: ", current_accuracy)
    print("Precision: ", current_precision)
    print("Recall: ", current_recall)
    print("F1: ", current_f1)
    print("AUC-ROC: ", current_aucroc)

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
For:  RF
Accuracy:  0.9774086378737542
Precision:  0.9649122807017544
Recall:  0.8549222797927462
F1:  0.9065934065934066
AUC-ROC:  0.9829078731201821

For:  GBDT
Accuracy:  0.9554817275747508
Precision:  0.9565217391304348
Recall:  0.6839378238341969
F1:  0.797583081570997
AUC-ROC:  0.9631243681283962
```

Emily: This is the link to my notebook with the models assigned:

https://github.com/AliceLiu17/csc448_final/blob/main/code/emily/data_analysis.ipynb

To create my SVM model, I had initially converted the data in processed_email into string because of an error that had occurred when running it on my end. I then split the data into training and testing sets where the randomizing was set to 42. I had initialized a TfidfVectorizer in order to convert text data into numericals. The SVM model is created through the use of the SVC class. The code proceeds to train the model and generate its prediction. It then prints out the evaluations like the accuracy score and the classification report which includes F1-score, precision, recall, and support.

In [20]:
```
# SVM model on the preprocessed data from above

# need to convert into string -> error occurred when running
data['processed_email'] = data['processed_email'].apply(lambda x: ' '.join(x) if isinstance(x, list) else x)

# split data and test
X_train, X_test, y_train, y_test = train_test_split(data['processed_email'], data['label'], test_size=0.2, random_st

tfidf_vectorizer = TfidfVectorizer()
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

# create svm model
model = SVC(kernel='linear')
model.fit(X_train_tfidf, y_train)
predictions = model.predict(X_test_tfidf)

# evaluate the model's accuracy in a report style/format
print("SVM Model")
print(f"Accuracy: {accuracy_score(y_test, predictions)}")
print(classification_report(y_test, predictions))
```

```
SVM Model
Accuracy: 0.9782067247820673
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1376
           1       0.98      0.87      0.92       230

    accuracy                           0.98      1606
   macro avg       0.98      0.93      0.95      1606
weighted avg       0.98      0.98      0.98      1606
```

To create my Logistic regression model, I had again initially converted the data in processed_email into string because of an error that had occurred when running it on my end. I then split the data into training and testing sets where the randomizing was set to 42. I had initialized a TfidfVectorizer in order to convert text data into numericals. The logistic regression model is created through the use of the LogisiticRegression class. The code proceeds to train the model and generate its prediction. It then prints out the evaluations like the accuracy score and the classification report which includes F1-score, precision, recall, and support.

```
weighted avg       0.98      0.98      0.98      1606
```

In [19]:
```python
# Logistic Regression model on the preprocessed data

# need to convert this to string -> error had occurred
data['processed_email'] = data['processed_email'].apply(lambda x: ' '.join(map(str, x)) if isinstance(x, list) else

# split data and test
X_train, X_test, y_train, y_test = train_test_split(data['processed_email'], data['label'], test_size=0.2, random_st

tfidf_vectorizer = TfidfVectorizer()
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

# creating Logistic Regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train_tfidf, y_train)
predictions = model.predict(X_test_tfidf)

# evaluate the model's accuracy in a report style/format
print("Logistic Regression Model")
print(f"Accuracy: {accuracy_score(y_test, predictions)}")
print(classification_report(y_test, predictions))
```

```
Logistic Regression Model
Accuracy: 0.9526774595267746
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      1376
           1       0.97      0.69      0.81       230

    accuracy                           0.95      1606
   macro avg       0.96      0.84      0.89      1606
weighted avg       0.95      0.95      0.95      1606
```

Lily:

This is the link to my notebook with the models assigned:

https://github.com/AliceLiu17/csc448_final/blob/main/code/lily/Modeling.ipynb

I initialize two vectorizer objects: CountVectorizer and TfidfVectorizer. CountVectorizer transforms text documents into a matrix where rows represent documents and columns represent token counts. TfidfVectorizer, on the other hand, converts raw documents into a TF-IDF matrix, where TF-IDF values represent term importance. The maximum number of features is set to 3000, controlling the vocabulary size. The code then proceeds to prepare data for model building. It transforms the 'processed_email' column in the DataFrame using TfidfVectorizer and sets it as the feature variable 'X', while the 'label' column becomes the target variable 'y'. The dataset is split into training and testing sets for both features and labels using train_test_split, with an 80-20 split ratio and a specified random state for reproducibility. Then I made the model for MNB and decision tree classifiers which I trained and evaluated.

```
# Initialize Multinomial Naive Bayes Classifier (MNB)
mnb = MultinomialNB()

# Initialize Decision Tree Classifier with a maximum depth of 5
dtc = DecisionTreeClassifier(max_depth=5)

# training data and evaluate on test data,
# returning accuracy and precision scores for the predictions
mnb.fit(X_train,y_train)
y_pred_mnb = mnb.predict(X_test)
accuracy_mnb = accuracy_score(y_test, y_pred)
precision_mnb = precision_score(y_test, y_pred)

dtc.fit(X_train,y_train)
y_pred_dtc = dtc.predict(X_test)
accuracy_dtc = accuracy_score(y_test, y_pred)
precision_dtc = precision_score(y_test, y_pred)
```

Then I made a classification report to see which model performed better. Here are the results below.

```
# For Multinomial Naive Bayes
print("Classification Report for Multinomial Naive Bayes:")
print(classification_report(y_test, y_pred_mnb))

# For Decision Tree Classifier
print("Classification Report for Decision Tree Classifier:")
print(classification_report(y_test, y_pred_dtc))
```

```
Classification Report for Multinomial Naive Bayes:
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1312
           1       0.98      0.80      0.88       193

    accuracy                           0.97      1505
   macro avg       0.98      0.90      0.93      1505
weighted avg       0.97      0.97      0.97      1505

Classification Report for Decision Tree Classifier:
              precision    recall  f1-score   support

           0       0.94      0.98      0.96      1312
           1       0.85      0.60      0.71       193

    accuracy                           0.94      1505
   macro avg       0.90      0.79      0.83      1505
weighted avg       0.93      0.94      0.93      1505
```

After I wanted to test out if my model really works with two examples one is spam and one is not spam. MNB predicted it correctly, it is a spam email the accuracy for that model was higher as well

so it did recognize it whereas the decision tree predicted it wrong. Then for both, they predicted not spam email correctly.

```
# testing if both models work with sample text
sample_text = "Congratulations! You've won a free vacation to an exotic island. Claim your prize now by clicking

# Fit and transform the sample text
sample_text_transformed = tfid.transform([sample_text])

# Test with Multinomial Naive Bayes
predicted_mnb = mnb.predict(sample_text_transformed)
print("Predicted class for sample text using Multinomial Naive Bayes:", predicted_mnb)

# Test with Decision Tree Classifier
predicted_dtc = dtc.predict(sample_text_transformed)
print("Predicted class for sample text using Decision Tree Classifier:", predicted_dtc)

# MNB predicted it correctly, it is a spam email the accurancy for that model was higher as well so it did recgon
# it where as decision tree predcicted it wrong
```

```
Predicted class for sample text using Multinomial Naive Bayes: [1]
Predicted class for sample text using Decision Tree Classifier: [0]
```

```
# testing if both models work with sample text
sample_text = "Hello Richard, please send in your report EOD."

# Fit and transform the sample text
sample_text_transformed = tfid.transform([sample_text])

# Test with Multinomial Naive Bayes
predicted_mnb = mnb.predict(sample_text_transformed)
print("Predicted class for sample text using Multinomial Naive Bayes:", predicted_mnb)

# Test with Decision Tree Classifier
predicted_dtc = dtc.predict(sample_text_transformed)
print("Predicted class for sample text using Decision Tree Classifier:", predicted_dtc)

# both predicts not spam email correctly
```

```
Predicted class for sample text using Multinomial Naive Bayes: [0]
Predicted class for sample text using Decision Tree Classifier: [0]
```

Combining all 3 notebooks together the detailed implementation of the modeling process can be found in "Model Building.ipynb" notebook, which looks like this:

In [3]:
```
# Initialize a CountVectorizer object
# CountVectorizer converts a collection of text documents into a matrix of token counts
# Each row represents a document, and each column represents the count of a particular token in the document
cv = CountVectorizer()

# Initialize a TfidfVectorizer object with a specified maximum number of features
# TfidfVectorizer converts a collection of raw documents to a matrix of TF-IDF features
# TF-IDF (Term Frequency-Inverse Document Frequency) represents the importance of each term in the document corpu
# 'max_features' sets the maximum number of features (terms/words) to be used, limiting the vocabulary size
tfid = TfidfVectorizer(max_features=3000)
```

In [4]:
```
# Declaring x and y values for model building

# Use the previously initialized TfidfVectorizer to transform the 'processed_email' column in the DataFrame
# tfid.fit_transform() transforms the text data into a TF-IDF matrix
# 'processed_email' likely contains preprocessed text data (cleaned, tokenized, etc.)
X = tfid.fit_transform(df['processed_email'])

# Extract the target variable ('label' column) from the DataFrame and convert it into a NumPy array
# df['label'].values returns the values of the 'label' column as a NumPy array
y = df['label'].values
```

In [5]:
```
# Split the dataset into training and testing sets for both features (X) and labels (y)
X_train, X_test , y_train, y_test = train_test_split(X,y,test_size = 0.20, random_state = 45)
```

In [6]:
```
# Initialize Support Vector Classifier (SVC) with a linear kernel
svc = SVC(kernel='linear')

# Initialize Multinomial Naive Bayes Classifier (MNB)
mnb = MultinomialNB()

# Initialize Decision Tree Classifier with a maximum depth of 5
dtc = DecisionTreeClassifier(max_depth=5)

# Initialize Logistic Regression Classifier using 'liblinear' solver and L1 penalty
lrc = LogisticRegression(solver='liblinear', penalty='l1')

# Initialize Random Forest Classifier with 50 estimators and a random state of 2
rfc = RandomForestClassifier(n_estimators=50, random_state=2)

# Initialize Gradient Boosting Classifier with 50 estimators and a random state of 2
gbdt = GradientBoostingClassifier(n_estimators=50, random_state=2)
```

In [7]:
```python
# Making a dictionary for the models for easy access
models = {
    'SVC': svc,
    'NB': mnb,
    'DT': dtc,
    'LR': lrc,
    'RF': rfc,
    'GBDT': gbdt
}
```

In [8]:
```python
# Function to train a list of classifiers (clfs) on training data and evaluate on test data,
# returning accuracy and precision scores for the predictions
def train_classifier(clfs, X_train, y_train, X_test, y_test):
    models.fit(X_train,y_train)
    y_pred = models.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    return accuracy , precision
```

In [9]:
```python
accuracy_scores = []  # List to store accuracy scores for each model
precision_scores = []  # List to store precision scores for each model

# Iterate through each classifier in the 'models' dictionary
for name, models in models.items():
    # Train the current model, calculate accuracy and precision scores
    current_accuracy, current_precision = train_classifier(models, X_train, y_train, X_test, y_test)

    # Print the scores for the current model
    print()
    print("For: ", name)
    print("Accuracy: ", current_accuracy)
    print("Precision: ", current_precision)

    # Append the scores to the respective lists for future analysis
    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
For:  SVC
Accuracy:  0.9774086378737542
Precision:  0.9595375722543352

For:  NB
Accuracy:  0.9727574750830564
Precision:  0.9810126582278481

For:  DT
Accuracy:  0.9348837209302325
Precision:  0.8518518518518519

For:  LR
Accuracy:  0.9674418604651163
Precision:  0.9556962025316456

For:  RF
Accuracy:  0.9774086378737542
Precision:  0.9649122807017544

For:  GBDT
Accuracy:  0.9554817275747508
Precision:  0.9565217391304348
```

Analysis

We found that the model that does the best is Random Forest due to our evaluation metrics for classifiers. Our metrics include accuracy, precision, recall, F1 score, and AUC-ROC.

- *Accuracy* is the count of all the predictions we got correct divided by the total number of predictions so the percent of predictions we got correct.
    - A higher accuracy indicates better overall performance.
- *Precision* measures the accuracy of positive predictions made by a model so what proportion of positive identifications was actually correct? Out of all the times our model says "YES", what percentage was correct.
    - A higher precision means fewer false positives
- *Recall* measures the ability of a classifier or model to identify all relevant instances, specifically positive instances so what proportion of actual positives was identified correctly? Out of all the times THE ACTUAL was "YES", what percentage did you correctly label.
    - A high recall means fewer false negatives
- *F1 Score*: The 'harmonic mean' of precision and recall and can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0.
    - A high f1 score indicates better trade-off between precision and recall
- *AUC-ROC*: This represents the area under the receiver operating characteristic curve, which measures the model's ability to distinguish between positive and negative instances.
    - A higher ROC-AUC indicates better discrimination between classes.

```
For:  LR
Accuracy:  0.9674418604651163
Precision:  0.9556962025316456
Recall:  0.7823834196891192
F1:  0.8603988603988605
AUC-ROC:  0.9711511120940226

For:  RF
Accuracy:  0.9774086378737542
Precision:  0.9649122807017544
Recall:  0.8549222797927462
F1:  0.9065934065934066
AUC-ROC:  0.9829078731201821

For:  GBDT
Accuracy:  0.9554817275747508
Precision:  0.9565217391304348
Recall:  0.6839378238341969
F1:  0.797583081570997
AUC-ROC:  0.9631243681283962

For:  SVC
Accuracy:  0.9774086378737542
Precision:  0.9595375722543352
Recall:  0.8601036269430051
F1:  0.907103825136612
AUC-ROC:  0.9895385757614052

For:  NB
Accuracy:  0.9727574750830564
Precision:  0.9810126582278481
Recall:  0.8031088082901554
F1:  0.8831908831908831
AUC-ROC:  0.9809885631239732

For:  DT
Accuracy:  0.9348837209302325
Precision:  0.8518518518518519
Recall:  0.5958549222797928
F1:  0.7012195121951219
AUC-ROC:  0.8413469133072159
```

In our model building, we used a dictionary to store all the models we used and printed the evaluation metrics for each model. There is a screenshot above showing the results where

- NB is the Naive Bayes (multinomial naive bayes) model
- SVC is the SVM model
- LR is the Logistic regression model
- RF is the Random Forest model
- GBDT is the Gradient Boosting Model
- DT is the Decision Tree model

The best model was Random Forest because it got the highest scores for all evaluation metrics.

Random Forest:

- ➢ Accuracy: 97.7%
- ➢ Precision: 96.5%
- ➢ Recall: 85.5%
- ➢ F1 score: 90.7%

- AUC-ROC: 98.3%

Decision Tree:

- Accuracy: 93.5%
- Precision: 85.2%
- Recall: 60%
- F1 score: 70.1%
- AUC-ROC: 84.1%

The Random Forest model performed better than the Decision Tree model, and there were three main reasons why. Compared to a single Decision Tree, Random Forest lowers noise and overfitting by utilizing several trees and consolidating predictions. Unlike a single Decision Tree where it's dependent on certain features. Random Forest improves generalization due to its varied feature subsets and decreased connection between trees. Overall, Random Forest is a more reliable option for better categorization due to its skill at handling complexity and overfitting.

Moreover, Random Forest generally improves accuracy by reducing overfitting and capturing more complex patterns in the data; hence, accuracy score was higher. As for Precision, Recall, and F1 Score, the Random Forest leads to better values, especially when dealing with imbalanced datasets. The diversity in trees helps achieve a balance between precision and recall. Given the imbalance nature of our dataset, whose non-spam had a higher markup in our data in comparison to spam emails, this was beneficial. Additionally, for AUC-ROC, Random Forest's ability to handle diverse features and reduce overfitting often leads to a higher AUC-ROC score compared to a single decision tree.

Summary

The goal of our project was to improve the accuracy of our spam classification model. We were able to confirm the Random Forest model's fundamental function in our prototype by reaching an accuracy score of 97% and a precision of 96% using its model.

- **Datasets and Preprocessing:** We used two different datasets, "spam.csv" and "spam_or_not_spam.csv", which required meticulous planning in order to guarantee the consistency of the data to be able to combine the two into one. This involved eliminating duplication, dealing with NULL values, and using text processing methods for model compatibility like vectorization, removing common words, also known as stop words, and tokenization.
- **Model Exploration:** We explored six models – Naive Bayes (multinomial naive bayes), SVM, Logistic Regression, Random Forest, Gradient Boosting, and Decision Tree – each model selected based on how well it could handle particular email classification tasks.
- **Model Performance:** The Random Forest model demonstrated to be the most accurate and best precision compared to the other five models, achieving a 97% accuracy score and a 96% precision score.
- **User Interface Development:** We used the Voilà jupyter server extension to produce a working interface where users can test to see whether their text would be considered as spam or not. This is found in "Voila Implementation.ipynb"
    - Recording Uploaded on GitHub: voila_recoding.mov OR voila_recording.gif
    - The recording and some sample input strings can be found in README of the github and on the link below in Voila Implementation.

Overall, our results confirmed the importance of using a variety of models to improve the accuracy of email classification. The 97% accuracy rate attained with the Random Forest model highlights its effectiveness and provides a solid basis for further advancement in this modern issue.